(**Araştırma**)

EXPLORING AND IDENTIFICATION OF PASSENGERS' WEB SEARCH GOALS USING "TICKET" RELATED QUERIES IN THE AIRLINE MARKET: A GOOGLE TRENDS STUDY

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Abstract

The implications of information search behavior on the web have become clearer now that internet search engines data are publicly available. In this respect, understanding and exploring web search goals of users can lead search engines to provide better-personalized results, while enabling marketers to choose the right advertising objectives. It is of great importance that people's time-dependent web search goals of the purchasing of air tickets are revealed from a collective perspective in the airline market. Thus, this study aims to determine time-dependent web search goals of passengers for the airline market by examining different word variations in flight ticket queries. Thus, global search query data from different periods were obtained using Google Trends (GT). Independent samples t-test, One-Way ANOVA and MANOVA were performed to answer the research questions. According to the results of the research, passengers were mostly interested in using Google for transactional goals. This was followed by "locating" physical evidence in airline services. Besides, navigational searches of passengers appeared to differ significantly by hourly periods.

Keywords: web search goal, search behavior, Google Trends, airline market, flight ticket

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YOLCULARIN "BİLET" İLE İLİŞKİLİ SORGULARI KULLANILARAK HAVAYOLU PAZARINDAKİ AĞ ARAMA AMAÇLARININ KEŞFİ VE TANIMLANMASI: BİR GOOGLE TRENDS ÇALIŞMASI

Özet

Arama motorlarının verilerini kamuya açmasının ardından web üzerindeki bilgi arama davranışının etkileri daha anlaşılır bir yapı kazanmıştır. Bu bağlamda, kullanıcıların web arama amaçlarını anlamak ve keşfetmek, pazarlamacıların doğru hedeflere reklamcılık faaliyeti gerçekleştirmelerine olanak tanırken daha iyi kişiselleştirilmiş sonuçlar sağlamak için arama motorlarına da katkıda bulunabilmektedir. Dolayısıyla uçak bileti satın alınırken zamana bağlı web arama amaçlarının havayolu pazarında kolektif bir perspektiften ortaya konması büyük önem taşımaktadır. Bu çalışmanın amacı, uçak bileti sorgularında farklı kelime varyasyonlarını inceleyerek, havayolu pazarı için yolcuların zamana bağlı web arama amaçlarını belirlemektir. Bu amaçla Google Trends (GT) kullanılarak farklı zaman dilimleri için küresel arama sorgusu verileri elde edilmiş olup araştırma sorularına cevap vermek amacıyla bağımsız örneklem t-Testi, Tek Yönlü ANOVA ve MANOVA analizleri yapılmıştır. Araştırmanın sonuçlarına göre, yolcuların çoğunlukla Google'ı işlemsel amaçlar için kullandıkları belirlenmiştir. Bu amaçları, havayolu hizmetlerinde fiziksel kanıtları bulma niyeti takip etmiştir. Ayrıca, yolcuların navigasyonel aramalarının saatlik periyotlara göre önemli ölçüde farklılaştığı tespit edilmiştir.

Anahtar kelimeler: web arama amacı, arama davranışı, Google Trends, havayolu pazarı, uçak bileti

1.Introduction

With the development of web search engines, the Internet has given billions of consumers in many sectors the opportunity to search for information online. Looking at the search engine industry, Google holds more than 90% of its market share.[2] Google, with its "Google Trends" service, offers a time-based volume of data of searches made by internet users on specific topics. Collecting search query data and converting it into information is very important in making business decisions (Preis, 2013). Accordingly, Google made the results of search queries publicly available in 2009 (Carrière -Swallow and Labbe, 2011). Therefore, it is inevitable that such a large amount of data that emerge on Google, where 3.5 billion searches are done in just one day[3], will be used in consumer behavior research. The big data produced by consumer behavior, especially in the social media environment, can be used to learn and analyze the opinions of large focus groups on any product. In this way, information can be obtained about what consumers do, how they do, where and when they consume, and with whom they consume in the consumer decision-making process. Search engine queries are also one of the big data sources in the search process that emerged right after the problem is noticed in the consumer problem-solving process (Hofacker et al., 2016), and they can be considered as an important tool that has been used since 2005 (Choi and Varian, 2012) in analyzing consumer behavior.

Studies that deal with consumer and customer information search behavior from a collective perspective, using internet search engines as data sources, exist in many areas such as health (Brigo et al., 2014; Bragazzi et al., 2017; Dreher et al., 2018), science (Segev and Baram-Tsabari, 2012; Segev and Sharon, 2017), employment (Naccarato et., 2018), politics (Weeks and Southwell, 2010; Housholder et al., 2018), finance (Preis et al., 2013; Zeybek and Uğurlu, 2015; Ahmed et al., 2017), tourism (Önder and Gunter, 2016; Krsak and Kysela, 2016; Padhi and Pati, 2017; Dinis et al., 2017; Baldigara, 2019), beauty (Tijerina et al., 2018), meteorology and climate change (Lang, 2014; Leas et al., 2016).

The reason why internet search engines are used as data sources is to determine the search behavior of potential or actual consumers in real-time. In line with this, air passengers have theoretically been able to access a wide range of information about ticketing and booking over the Internet. Moreover, passengers can access such information without the support of travel agencies (Little et al., 2011, p, 122). Considering the examples given above, the literature contains few but effective studies in terms of examining web search behavior.

Web search behavior associated with information searching behavior (Wilson, 2000) refers to an internet user finding the desired information by interacting with the search engine on the web (Indartoyo et al., 2016). Studies dating back to the mid-90s have determined that the search for information was influenced by factors such as information need, domain knowledge, cognitive abilities, affective states, and demography (Hsieh-Yee, 2001). Although information need is suggested as one of the important reasons underlying web search behavior, Broder (2002) determined that non-informational needs may also be effective factors leading search behavior. According to Broder (2002), these factors can be listed as navigational, informational, and transactional goals. Rose and Levinson (2004)

2 https://www.smartinsights.com/search-engine-marketing/search-engine-statistics/ (Accessed 22/11/2019)
3 https://www.internetlivestats.com/google-search-statistics/ (Accessed 17/08/2020)

extended Broder's trichotomy by classifying them as subcategories and replaced transactional queries with "resource" searches to identify user search goals.

Understanding consumer goals within the web search behavior perspective is a significant task for advertising objectives (Schultz, 2020), development of further web search engines (Rose and Levinson, 2004), creating new knowledge, and also supporting content marketing decisions (Penela et al., 2017). Thus, understanding consumer web search behavior is of great importance in the airline industry, as in almost every service sector.

The airline industry is in the transportation sector, which has a critical role in today's economy with its contribution to growth and employment.[4] The size of the demand in the airline industry reached 4.54 billion boarded passengers in 2019.[5] Therefore, especially the travel searches made by the air passengers with search engines appear to be an important guide in the understanding of these people's behavior for this sector. In this respect, it is also important to identify and interpret the goals and interests of airline passengers using search engines.

The primary contributions of this study are to classify web search goals of users using the Google Trends portal and bridge the gap between consumer behavior and web search studies. Therefore, the first aim of this study is to determine and analyze the goals in the web search behavior of potential and actual passengers over four periods (hourly, daily, monthly, and yearly). Second, motivators that affect customer interest will be found out by using Rose and Levinson's (2004) framework that helps classifying queries from a web search engine to underlie the goals of user searches. The third objective is to explore (statistically) whether web search goals change over time. As such, the method, the results obtained, a discussion of the implications of the results, and the limitations and suggestions for future studies will take place in the following sections.

2.Related work and Research Questions

There is no limit to the topics searched on the web. In this sense, understanding web search goals of users ensure that the right algorithms and better interfaces can be used in search engines (Su et al., 2018) by obtaining more relevant results about queries (Kathuria et al., 2010). Consequently, search engine quality can be increased (Lee et al., 2005).

It is known that studies for web search goals are theoretically inspired by the Anomalous States of Knowledge (ASK) model (Belkin et al., 1982a; Belkin et al., 1982b). When these studies for determining and classifying web search objectives are examined, it can be seen that the research of Broder (2002) and Rose and Levinson (2004) has pioneered the literature with their structures.

To determine web search goals, some techniques such as interview (Rieh, 2003), survey (Broder, 2002; Li et al., 2006), query labeling (Ashkan et al., 2009), observations (Kellar et al., 2006), analyzing logs (Jansen et al., 2008; Mohasseb et al., 2014), automatic classification (Lee et al., 2005; Jansen et al., 2008; Kathuria et al., 2010; Hernández et al., 2012), and hybrid methods (Rose and Levinson, 2004) have been in the literature. Most of these previous studies used Broder's (2002) taxonomy, that is, classification. Moreover, in some studies

4 https://ec.europa.eu/jrc/en/research-topic/transport-sector-economic-analysis (Accessed 12/08/2020).

5 https://www.statista.com/statistics/564717/airline-industry-passenger-traffic-globally/ (Accessed 12/08/2020)

(Rose and Levinson, 2004; Kellar et al., 2006) this classification was expanded. For example, Kellar et al. (2006) examined informational search goals and classified them as seeking, exchange, and maintenance. Rose and Levinson (2004) summarized users' web search goals in three categories: informational, navigational, and resource. They divided these three main classes into subcategories according to the search goals of the users using search sessions.

What is more, uncovering the intensity of web search goals among the total queries is one of the main research questions in the studies. In this regard, many previous studies indicate that users have more tendency for informational needs. For instance, Rose and Levinson (2004) revealed that most of the queries were informational. In another study, Jansen and his colleagues (2008) reported that 80% of the total queries were informational goals, followed by navigational and transactional goals. Kathuria et al. (2010) determined that three-quarters of the total queries were informational and reported that transactional and navigational goals had equal shares among the rest. Hernández et al. (2012) classified queries manually and indicated that most of them were informational goals, followed by navigational and transactional goals. In contrast, some studies brought to light that navigational or transactional goals come to the fore in queries.

Rieh (2003) conducted an observational study on information seeking and found that locating a homepage of a web site, which might contain the desired information, was generally preferred to locate rather than find a certain web page directly. In another study, Ashkan et al. (2009) manually labeled most of the 1700 queries as navigational. Kellar et al. (2006) recorded participants' web search data that include 1192 task sessions involving 13,498 pages over the week. They reported that participants use the web mostly for transactions that have two distinct goals. The first one is the communication of information like posting to message boards. Second is the completion of online actions, such as online banking.

Based on all these studies, the identification and classification of web search goals of air passengers and determining weights of these goals in the total queries will contribute to the literature in two ways. First is to demonstrate how the GT data can be used to determine what goals air passengers search on Google. Second is to examine at what time periods these goals show differences. Therefore, the research questions of the study can be phrased as follows:

RQ1: What is the web search goal of air passengers who search "ticket" related queries on Google?

RQ2: What are the shares of each web search goals of air passengers in the total queries?

The purposes that users have when performing their searches are a result of the needs of their roles and it can change depending on time. One of the important dimensions of the search process is the time interval. Consumers exposed to similar advertisements can perform searches at different time intervals (Kiel and Layton, 1981). This was also clearly stated by Nagar and Suleman (2017). They explained the situation with an example from a computer science student who also likes sports. They stated that s(he) could search for sports and computer-related terms at different times and found out that the interest of a user for different topics can be time-sensitive. Thus, the third research question can be formulated as follows:

RQ3: What is the effect of time periods on web search goals of air passengers?

3.Methodology

3.1.Data

To answer research questions, GT was used to reach the results of ticket searches related to air travel performed globally between specific periods as past hour, past day, past week, past month, and past year. The data was retrieved on February 17, 2020. Google represents the qualitative data related to the queries by normalizing between 0-100. If this normalization is not applied, the top search volume in a specific geographical area will be consistently high (Brigo et al., 2014). The search criterion was limited to travel in order to obtain more accurate related queries. The geographical area where the search was done was selected as 'World' to represent users who search for tickets in the English language across air transportation. The time frame covering 2019 and 2020 includes hourly, daily, weekly, monthly, and yearly time intervals. When obtaining data for search volumes, possible queries about air tickets were examined with different variations. Accordingly, the search terms "air ticket", "flight ticket", "airline ticket", and "plane ticket" were used.

Totally, 421 top related queries with their metrics were obtained from the GT portal. One yearly query was removed from the dataset since the search volume of this query was incorrectly derived. Thus, 420 queries were totally captured for the dataset. In addition, the author captured time-dependent data. The number of related queries considering metrics of search terms and time periods was represented in Table 1.

Table 1. Number of related queries

Search Terms	Hourly	Daily	Weekly	Monthly	Yearly	Total
air ticket	25	25	25	25	25	125
airline ticket	1	25	25	6	24	81
flight ticket	18	25	25	25	25	118
plane ticket	-	25	25	21	25	96
Total	44	100	100	77	99	420

Finally, 421 top and rising related queries were manually coded according to their category. In accordance with the purpose of the study, the search index, which expresses the customer's interest in the search terms, was captured. On average, a top related query for the selected search terms generated 37,48 (SD=27,48) search index.

3.2.Variables

3.2.1.Passenger Interest

To identify passengers' interests the author used Google's scoring scale. In this sense, top related topics mean the most popular topics, which are relatively scaled by scoring between 0-100. A value of 100 means the most commonly searched topic also are searched for the selected term, and 50 represents a topic searched by internet user half as often as the most popular term, and so on.[6]

6 https://trends.google.com (Accessed 22.02.2020)

3.2.2.Navigational Goals

The access of a user to information is very effective in satisfying the relevant need. Accordingly, users are sometimes aware of the information they are seeking and can focus on one result and complete their search after accessing this information. The fact that users are aware of the existence of a web page that they are looking for pushes them to search for navigational goals that will meet their informational needs (Lewandowski, 2011).

The goal for navigational search is to find a specific website. This web page may belong to a person, an organization, or the user may believe that this page may exist (Jansen et al., 2008).

Rose and Levinson (2004) defined navigational goal as "demonstrating a desire by the user to be taken to the home page of the institution or organization in question." In line with this work, the author manually categorized 421 top related topics for air travel as navigational or not navigational, representing 1 and 0, respectively. For example, topics about an airline or agency name were categorized as 1.

3.2.3.Informational Goals

The need for information emerges after the process of guessing the text related to the information the user needs. From the point of view of the use of information retrieval systems, this need can be defined in a special way by the user or fulfilled by interacting with the text (Belkin, 1993).

The intention for information search emerges as the search for a specific topic in data, text, document or multimedia formats depending on the researcher's information needs (Jansen et al., 2008). Rose and Levinson (2004) stated that informational queries are related to the purpose of collecting information about a topic and classified these searches into five subcategories as "directed" (closed and open), "undirected", "advice", "locate", and "list". "Directed" informational queries represent the goals that the user has already in mind and wants to learn something special about a topic that gets a single answer (closed) or requires open-ended questions. The "undirected" queries consist of topics that users may want to learn anything. In addition, "locate" describes user's goal as obtaining some real-world service or product (e.g., phone card). Furthermore, users would like to "list" some suggested web sites to achieve an unspecified goal such as buying X.

The author classified "ticket" related queries considering Rose and Levinson's (2004) descriptions and examples mentioned above. In this respect, the categorization of queries with examples is represented below:

-Directed informational queries include the words such as "fare", "price", "rates", "cost", "promo", "cheapest", "most" and/or "status". Also, queries directing "what if" or "what happens" questions have been added in this category. For example, the "wrong birthday on airline ticket" was regarded by the author as "what happens when the wrong birthday is written on airline ticket," which is associated with an informational query.

- Queries, including only city names, are regarded as "undirected" requests.

- For the "advice" category, queries including questions starting with "how" and "can" which means that the users want to get advice or ideas, were used. Also, the words "free" "offer" expressing the suggestions were regarded as advice.

- Special brands' tickets, tour packages, just "flight ticket" or "online ticket" queries are added to "locate" class.

- "List" category involves the query such as, "flight tickets" to a special origin/destination city, "cheap ticket", "flights" or "agencies" that are considered by the author as requesting the list of some suggested websites offering cheap tickets or flights.

3.2.4.Transactional Goals

Transactional goals begin when a user enters a query about a resource in the search engine. In this process, the user may have concerns about interacting with the site or perform a transaction, such as downloading software, music or videos, access to entertainment, sending of postal cards, and shopping (Herrera et al., 2010).

Transactional, also known as "resource" queries, represents a goal that needs to be fulfilled by obtaining something from websites. These queries are classified into four categories which are "download" used to install something on the computer, "entertainment", used to enjoy the items shown on the result page, "interact", used to exploit a program on the web site founded, and "obtain", used to read something on the screen (Rose and Levinson, 2004). In this respect, the labeling process was applied considering specific terms related to these classes as represented below:

- For the "download" category, queries containing terms such as "template", "app", "download", "print" were used.

- For the "interact" category, queries including "booking", "cancel", "confirmation", "buy", "sale", "check", and "generator" with the term "ticket" or "flight" were taken into account.

- Queries, such as "fake" and "dummy" were labeled with the "entertainment" category.

3.3.Descriptive Statistics

In line with the purpose of the study, the top queries obtained from the GT are divided into main categories and subcategories by considering time periods. The numbers and percentages of these categories in the total query are represented in Table 2. In general, transactional search goals had the highest interest (search volume) share among total queries on average with interaction (M=45.1) and was followed by subcategories of informational and navigational goals.

The "locate" category, which refers to reaching physical evidence for the service provided in the airline market, had the highest search interest (M=43.9) among informational queries. This was followed by "directed" (M=43.2), "list" (M=30.4), navigational goals (M=27.2), "undirected" (M=21.8), "download" (M=16.0), "advice" (M=12.7), and "entertainment" (M=12.5) goals. Also, it was determined that "locate" queries in hourly (M=44.6) and monthly (M=47.0) searches, "interact" (M=47.4) queries in daily searches, "directed-informational" queries in weekly (M=48.8) and yearly (M=53.4) searches came to the fore.

Table 2. Time-dependent descriptive statistics of labeled queries

Category**	Subcategory**	Total		Hourly		Daily		Weekly		Monthly		Yearly	
		N	SV* ($\bar{X}$)	N	SV ($\bar{X}$)	N	SV ($\bar{X}$)	N	SV ($\bar{X}$)	N	SV ($\bar{X}$)	N	SV ($\bar{X}$)
Navigational	Navigational	120	27.2	26	23.9	27	28.7	25	27.4	20	30.1	22	26.7
	Non	300	41.7	18	44.3	73	38.6	75	41.3	57	39.0	77	46.5
Informational	Directed	56	43.2	6	32.5	10	40.5	12	48.8	14	34.9	14	53.4
	Undirected	6	21.8	-	-	2	20.5	2	23.0	-	-	2	22.0
	Advice	3	12.7	3	12.7	-	-	-	-	-	-	-	-
	Locate	119	43.9	10	44.6	29	41.1	32	43.1	21	47.0	27	45.3
	List	124	30.4	3	29.3	37	28.6	30	29.5	20	26.6	34	35.4
	Non	112	37.4	22	29.6	22	40.6	24	36.9	22	37.0	22	43.1
Transactional	Download	1	16.0	-	-	-	-	1	16.0	-	-	-	-
	Entertainment	2	12.5	-	-	1	13.0	-	-	1	12.0	-	-
	Interact	64	45.1	10	40.7	12	47.4	15	43.8	13	43.2	14	49.3
	Non	353	36.4	34	29.8	87	34.6	84	37.0	63	35.7	85	40.9

* Search volume

** Derived from Rose and Levinson's (2004) study

In Table 3, descriptive statistics of the search volumes for the search goals of passengers in all categories are presented. Accordingly, it has been revealed that annual search queries have the highest average. These queries appear to be followed by weekly, monthly, daily, and hourly searches, respectively. Therefore, ticket related searches in the airline market are not directly proportional to the width of the time interval.

Table 3. Time-dependent descriptive statistics of search volumes

Time period	Search Volume	
	Mean	Std. **Dev**.
Hourly	32.25	30.17
Daily	35.9	25.76
Weekly	37.82	27.43
Monthly	36.65	29.54
Yearly	42.09	26.03
Total	37.57	27.45

3.4.Model Development

One of the purposes of this study is to examine time-dependent navigational, informational, and transactional search goals of passengers in terms of search interest. For this purpose, web search goals of the users who are accepted as potential or existing passengers were manually labeled taking into consideration the search queries derived from the GT. In the study, independent sample t-test, one-way analysis of variances (ANOVA), and multivariate analysis of variances (MANOVA) were performed according to the data type in order to understand whether dependent and independent variables differ from each other. The models and related variables are shown in Table 4.

Table 4. Model developments for variables in the dataset

Model	Type of variable(s)	Variable(s)
t-test	Test variable	Search volume
	Grouping variables	Navigational goals
		Transactional goals
ANOVA	Dependent variable	Search volume
	Factor	Informational goals
MANOVA	Dependent variables	Navigational goals
		Informational goals
		Transactional goals
	Factor	Time

"Directed", "locate" and "list" categories were used for the informational class. For transactional goals, only interact were considered. The subcategories "undirected" and "advice" under the information class, and "download" and "entertainment" under the transactional class were excluded because of an insufficient number of observations. Hence, 408 observations were preferentially taken for the analysis.

4.Results

To determine whether there is a significant difference in the time-dependent interest (search volumes) of the passengers based on the web search goals, the t-test, ANOVA, and MANOVA analyzes were performed by using the SPSS (IBM, 2019) package program. A T-test is used to examine group differences on each variable separately (Tabachnick and Fidell, 2013). ANOVA that was introduced by Fisher (Fisher, 1973) is used to compare statistical differences between two variables, and MANOVA is a suitable analysis to compare more than two groups (Tabachnick and Fidell, 2013). The T-test is used. Thus, the relationship between variables with two groups and search volume is represented in Table 5.

Table 5. The t-test results of the navigational and transactional goals

Variable	Groups	N	Mean	Sig.
Navigational	Navigational	119	27.43	0.000
	Non-navigational	289	42.58	
Transactional	Interact	63	45.71	0.018
	Non-transactional	345	36.78	

* Search volume is considered as the test variable

Search volume differs by navigational and transactional search goals at 0.000 and 0.018 significant level, respectively ($p < 0.05$). According to this analysis, while navigational searches attract less interest, searches for interaction have more search volume.

One-way ANOVA results shown in Table 6 indicate the differences in search volume index among the four groups (directed, locate, list, and non-transactional) under the informational goals.

Table 6. The ANOVA results for search volume

Informational Queries	N			Mean
Directed	56			43.23
Locate	119			43.94
List	124			30.39
Non-informational	109			38.09
	Sum of Squares	**Mean Square**	**F**	**Sig.**
Between Groups	12910.251	4303.417		
Within Groups	297283.072	735.849	5.848	0.001
Total	310193.324			

"Locate" searches, which represent the search for products or services related to air transportation, had the highest search volume (43.94) on average. These searches were followed by "directed-informational" (queries on a specific topic) (43.23), "non-informational" (38.09), and "list" (the keywords about listing flights, prices, or agents) (30.39). These differences were found statistically significant ($F= 5.848$; $p= 0.001$; $p < 0.05$).

Post-hoc tests were conducted to determine which queries were among these significant differences. Since the assumption of homogeneity of variances was violated, Games-Howell (1976) post-hoc test was adopted. Based on the results, "list" queries are classified as directed, locate, and non-informational queries at the level of 0,05 considering search interest.

For the purposes of the study, each of the top queries associated with search terms was obtained with the timestamp. It was examined whether web search goals differ by time. Thus, the mean and standard deviation values were represented in Table 7.

Table 7. Descriptive statistics of dependent variables

Dependent variable	Time	N	Mean	Std. Dev.
Navigational	Hourly	41	1.39	0.49
	Daily	97	1.72	0.45
	Weekly	97	1.74	0.44
	Monthly	76	1.74	0.44
	Yearly	97	1.77	0.42
Informational	Hourly	41	3.00	1.18
	Daily	97	2.71	0.92
	Weekly	97	2.66	0.98
	Monthly	76	2.63	1.08
	Yearly	97	2.66	0.99
Transactional	Hourly	41	1.78	0.42
	Daily	97	1.88	0.33
	Weekly	97	1.85	0.36
	Monthly	76	1.83	0.38
	Yearly	97	1.86	0.35

MANOVA was conducted to determine the impact of time-variable on web search goals. According to the results, the assumption of homogeneous variance-covariance matrices was accepted based on Box's test (F= 0.763, p= 0.787; p > 0.05) and proceeded with the MANOVA test (Huberty and Petoskey, 2000). As Table 8 exhibits, it was found that the navigational search goal of users appeared to differ significantly by time periods considering search volume (Wilks' Lambda= 0.005, F= 6.013; p= 0.000; p < 0.05).

Table 8. MANOVA results for time variable

Web Search Goal	Type III Sum of Squares	df	Mean Square	F	P	η_p^2
Navigational	4.747	4	1.187	6.013	0.000	0.056
Informational	4.371	4	1.093	1.071	0.370	0.011
Transactional	0.296	4	0.074	0.563	0.690	0.006

Next, Levene's (1960) test for homogeneity of variance was carried out to choose proper post-hoc analysis. Thus, this test proved statistically significant for navigational (p= 0.026; p < 0.05) and informational (p= 0.013; p < 0.05) variables, therefore, the Games-Howell test was implemented. For transactional queries, group variances were homogeneously distributed (p= 0.080; p > 0.05), and Tukey (1953) was selected as a post-hoc test.

According to the Games-Howell test results, it was found that informational and transactional searches do not show a significant difference (p> 0.05) depending on time. On the other hand, it has been revealed that hourly searches show significant differences in navigational searches compared to other time periods (day, week, month, year). In other words, looking at mean differences (MD) of the variables, users showed more tendency to the "navigational" searches in annual (MD= -0.3830), weekly (MD= -0.3520), monthly (MD= -0.3466), and daily (MD= -0.3314) periods. These descriptive statistics are represented in Table 9.

Table 9. Multiple comparisons for post-hoc tests

Dependent Variable	Test	Time (i)	Time (j)	Mean Diff. (i-j)	Sig.
Navigational	Games-Howell	Hour	Day	-0.3314	0.004
			Week	-0.3520	0.002
			Month	-0.3466	0.003
			Year	-0.3830	0.000
Informational	Games-Howell	Hour	Day	0.2887	0.634
			Week	0.3402	0.489
			Month	0.3684	0.467
			Year	0.3402	0.492
Transactional	Tukey	Hour	Day	-0.0958	0.616
			Week	-0.0649	0.873
			Month	-0.0485	0.959
			Year	-0.0752	0.800

5.Conclusion and Implications

With the advent of web technology, search engines are able to offer personalized results in response to user searches, by defining web search goals and classifying them correctly. Although a large part of the studies investigated the information-seeking behavior of users in different profiles, it is important to address the issue in terms of air passenger.

One of the probable contributions of this study to the literature is determining web search goals of air passengers who search for "ticket" related top queries on Google. To reach all possible queries, four different combinations of keywords (air ticket, airline ticket, flight ticket, plane ticket) were entered to the GT portal. Then, the author obtained GT data to answer the developed research questions.

Regarding RQ1 and RQ2, time-depended queries were manually labeled based on the framework of Rose and Levinson (2004), and it was found that most of the labeled queries submitted by passengers were interactional considering the average search volume data. It appears that the air passengers aimed to interact with the web pages they wanted to reach while choosing some keywords, such as booking, confirmation, or buying a ticket. Such queries might provide the transactions desired to be carried out on an airline web page after the search is done. Compared to these queries, the "locate", which is one of the subcategories of informational goals and expresses tangible evidence for airline services like tour package, was in second place in terms of passenger interests. Passengers were also inclined to directed-informational queries, including superlative adjectives or "what if" keywords, and list the results. These were followed by navigational goals. Next, "entertainment" queries containing some keywords, such as "fake" and "dummy", received less attention than other searches.

Many previous studies showed that the queries were mostly informational (Rose and Levinson, 2004; Jansen et al., 2008; Kathuria et al., 2010; Hernández et al., 2012). In contrast, there are also studies that found that navigational and transactional goals attracted more attention (Rieh, 2003; Ashkan et al., 2009). The results of this study are in line with the findings of Kellar and his colleagues (2006), who found that the transactions were the most frequent task.

To answer the RQ3, the effects of time periods on web search goals were examined. According to the findings, it was found that only navigational goals differ by time periods. As stated in the previous sections, navigational queries are made by entering the company names into the search engine. In other words, navigational searches are used to reach a specific home page that is already in the user's mind (Rose and Levinson, 2004). This can be an indication that air passengers are sensitive to time. Likewise, the fact that the hourly searches were mostly effective on navigational queries was another important finding of the study.

Examining the web search goals of users has several implications in the marketing area where consumer behavior is studied. First, determining and classifying the web search goals can take into account consumer needs and levels of satisfaction in the design of companies' web pages as well as search engines (Broder, 2002). To the best knowledge of the author, this is the first study that determines the web search behavior of air passengers using GT data. It should be noted that many factors, such as an individual's knowledge and experience and/or decision-making stage, play key roles in search queries (Pan et al., 2011). Thus, this study can contribute to the understanding of air passengers' behavior with the results. One of these is that air passengers search on Google mostly for informational goals. Air passengers search for locating special tour packages, a particular topic, or origin/destination cities. This may give airline marketing managers and SEOs a hint of methods such as promoting their destinations or choosing the right words that can be derived from GT data to describe their pages, which can get to the top of Google searches.

Second, the study used four possible combinations of "ticket" related queries in the airline market and obtained top related queries from GT. Manuel labeling was done in such a way that it highly represents the class in which the user queries are placed during the research. This suggests that potential or actual passengers choose words based on the type of information they need when entering terms into the search engine. It is known that queries have an undeniable role in web-based advertisements, and a combination of such queries may be adjusted by advertisers (Schultz, 2020). Thus, airline marketers will be able to find clues about keywords that will enable them to make effective web ads by following the process in the study.

Third, "different people have different topics and time preferences, and to better profile, the users, their complex periodic interest in topics needs to be known (Nagar and Suleman, 2019). Most of the topics over the web are searched regularly and time-dependent (Nagar and Suleman, 2017). The rise of online information seeking also requires airlines to design their web pages to respond to this behavior. The results of this study give some useful insight into the understanding of the air passengers' time-dependent search goals. Thus, understanding of which topics are searched by which users and at which times on the web can give opportunities to provide more personalized results in the airline market. In this study, only navigational search volumes differ significantly depending on time, indicating that the passenger already has a brand in mind while searching for a ticket. In this case, the implementation of advertising efforts that will create brand awareness for all users in the early stages of the ticket search process can be inspiring.

Briefly, the continuous analysis of the search behavior of airline passengers over the web will contribute to airline companies having a better understanding of their customers. This ability can help businesses intelligently design web pages, advertise to the right targets, and personalize ads that appear on the search engine.

6.Limitations and future research

There are some limitations in this study that should be addressed. First, web search behavior for air travel was analyzed using the terms "air ticket" "airline ticket", "flight ticket," and "plane ticket" via Google Trends. The search category and geographical region were limited as 'travel' and 'World', respectively. These limitations may restrict the generalizability of the research. Hence, in future studies, obtaining search volumes offered by other search engines in different categories, and by using local languages, would contribute to consumer behavior research in airline marketing literature. Second, since it is the most popular search engine in the market, Google was used in determining web search goals. Thus, it would be helpful to use the data of different search engines, e.g., Yandex and Bing, in the future studies due to the fact that the weights of each search goal in the total queries may vary according to the type of search engine or different data sets (Lewandowski, 2011). Third, 408 number of observations were analyzed to detect the relationship between web search goals, search volume, and search time. This dataset is not large enough to increase the validity and reliability of the statistical analysis used in this study. Consequently, enlarging the size of the data set will improve future studies. Finally, determining web search goals for other sectors with queries related to their product categories is very important to extend this study and to encourage researchers to use web search data in their studies.

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